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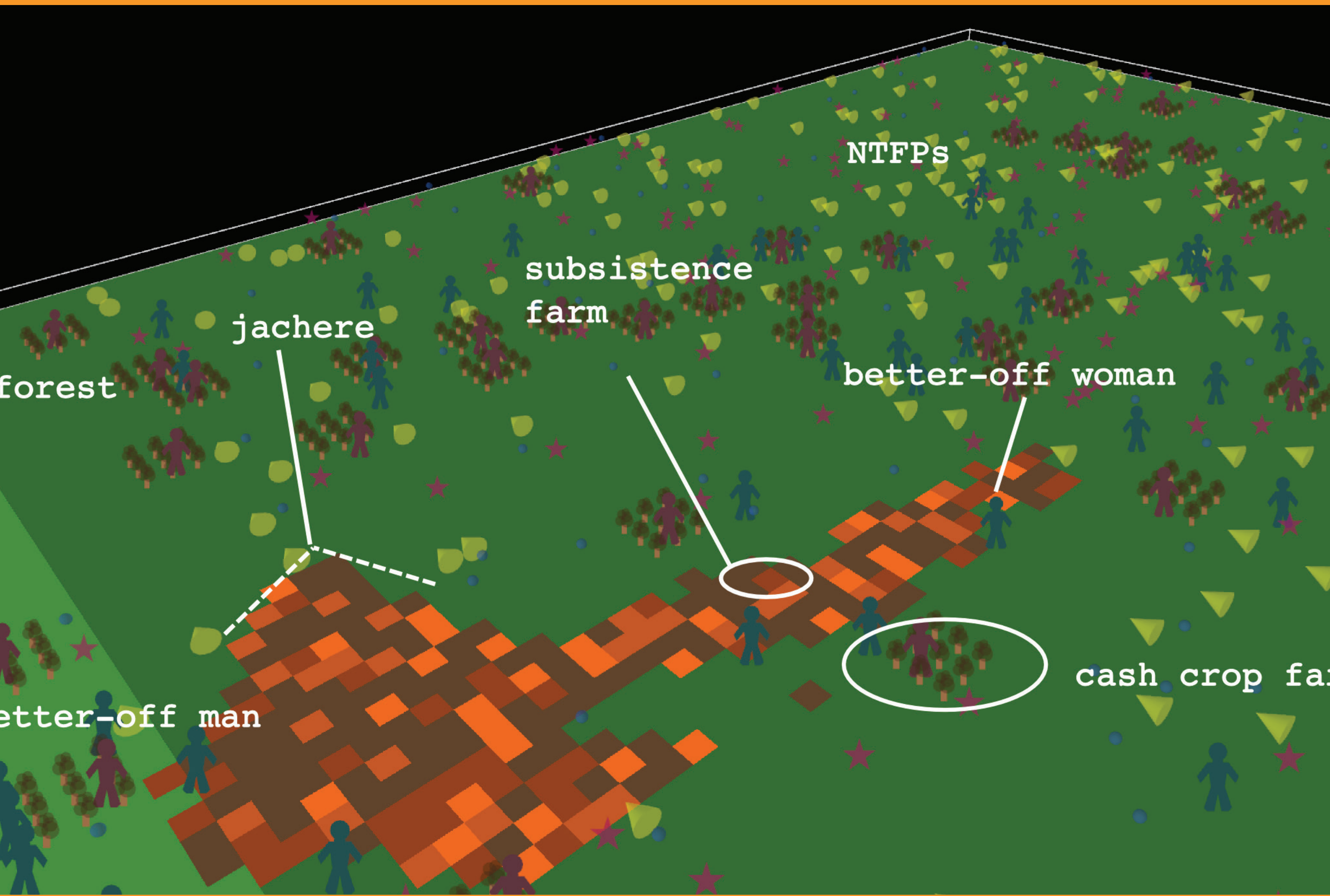

Agent-based modelling: A tool for addressing the complexity of environment and development policy issues

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Cover photo: A screenshot from an agent-based model developed by the authors for a study in Cameroon.

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ABSTRACT

Integrated policy problems call for integrated analysis. However, micro and macro approaches imply differences of perspective that conventionally have not been easy to unify. This paper introduces agent-based modelling (ABM) as one potentially useful tool for linking these aspects. ABM describes the system at the level of the social actors within it – that is, the individual entities, each with their own goals, values, rules, information, knowledge, strategies and social context. By doing this, ABM can help address the complexity of modern policy problems, particularly when used alongside other methods. The purpose of this paper is to explain ABM and its applications, to help model users determine whether this approach could be useful in their own work. Motivated by the observation that there is inadequate briefing material on the method, we explain ABM and then address four of the most common questions raised when appraising it for research on sustainable development. We draw on examples of SEI research using ABM for generating insights into a range of policy problems: the climate resilience of agroforestry livelihoods in Cameroon, energy policy and biofuels in Malaysia, sustainable livelihoods in small-scale fisheries in Kenya, and natural hazard disaster preparedness. By linking the example studies to the common questions, we further illustrate key lessons and findings in order to better inform readers.

CONTENTS

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1. INTRODUCTION

The integrated nature of sustainable development policy problems makes them challenging to assess scientifically. Studies need to look at the big picture, considering linkages within and across systems and the wider context. At the same time, it is important to understand the socio-economic and behavioural aspects of a problem – to learn, for example, what communities value most, or what business incentives are most effective. For those kinds of insights, a bottom-up approach is often needed.

Methods for both top-down and bottom-up analyses are well established. However, connecting the two to determine whether a policy strategy is robust can be very difficult, as it requires integrating insights from multiple disciplines and ways of thinking. Including multiple approaches greatly complicates an analysis and can result in contradictions due to differences in assumptions, concepts, terminology and outlooks. To ensure a coherent assessment, these differences have to be reconciled, either by aligning key elements, or by de-emphasizing areas where there is no clear answer.

Complex systems approaches, based on more recent theories and models, may overcome these sorts of problems by effectively bridging between micro and macro aspects. They can also address some common critiques: for instance, that models are too simple or too uniform to be useful in reality. Complexity approaches avoid overly reductionist assumptions: they allow for more diversity, interdependency, and a wider range of uncertainty and surprises. This working paper focuses on one such approach, agent-based modelling (ABM), as a potentially useful tool for applying a complex systems lens to sustainable development problems. We show how complexity is tackled with ABM, and address some of the critical questions underpinning ABM and the main insights that it can offer.

Our aim is to provide guidance and identify some lessons for using ABM in the context of sustainable development. We are motivated by the observation that when discussing how complex systems science may provide knowledge useful for policy, the same sorts of questions come up: "Do I need an ABM?" and "How can stakeholders be included?" Yet interest in the method is not met with adequate briefing material on these issues. Our intended audience is model users – broadly those who design, manage and participate in modelling projects or commission or evaluate them – but also the potential model developer, student or professional dabbler in modelling. We hope to help these readers become better informed for deciding whether and how ABM could be useful.

2. WHAT IS COMPLEXITY, AND HOW CAN I STUDY IT WITH THIS METHOD?

Complexity science is not a single consistent theory or approach, but is made manifest in a set of different tools and techniques from different research disciplines. It is a useful lens to describe real-world policy situations, where formal analytic modelling reaches limitations of tractability. However, it should be understood that the underlying phenomena – the real-world complexity – are much more difficult to define. If complexity is taken to mean all systems that are not simple, it could include almost everything we encounter!

Complex system models have characteristics which can make them suitable analogies of complex systems themselves, but also make them difficult to understand fully:

- They have many component parts and therefore many local variables (which give many possible system states).

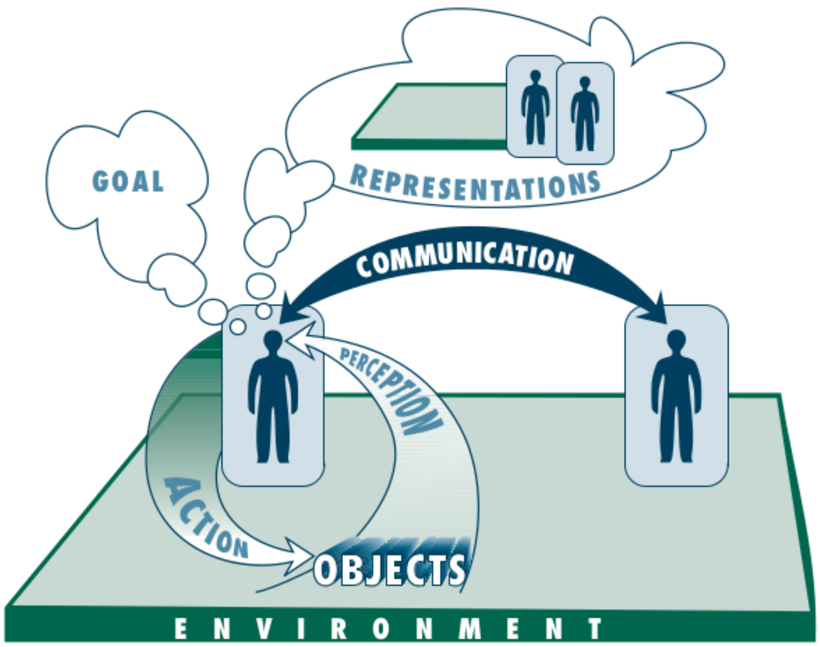
- They involve interactions among locally connected parts that need to be understood just as much as the functions of the individual components; they can contribute to significant non-linearities and emergent properties, for instance. Where traditional models reduce systems to easy-to-grasp components, complex system models may be difficult to interpret.
- They have macro-level properties that are not properties of any components of the system, are difficult to describe formally and – most relevant to policy research – can appear surprising, novel and unpredictable.

There are numerous reviews of complexity approaches across different research fields; for reference, see Box 1. Complexity research tends to rely mainly on modelling and interaction theory, but also qualitative as well as quantitative methods. ABM helps in understanding relationships and thus possible causal mechanisms in complex systems, by generating models of them from the bottom up.

Agent-based modelling concentrates on describing a social system at the micro-level of the actors within it. This is usually done using a computer model (program). The description for each agent includes a set of instructions or "rules". Agents also have goals and other internal information (knowledge, beliefs, values, etc.) which uniquely shape their actions. This bundling of data with instructions for agents allows them to be, in practice, coded as autonomous units representing different social entities. The agent descriptions are used as a template to create many copies and thereby populate a model (hence, ABMs are sometimes also known as multi-agent systems or multi-agent models).

In ABM, there is a focus on the micro-behavioural level, but models can include many or multiple types of agency at different levels of action, e.g. households, firms or local authorities. There is also a focus on interactions with other agents and interaction with the environment: ABMs have been used quite extensively to understand management and use of environmental resources, as well as adaptation processes under environmental change.

Figure 1: An illustration of the concept of agent-based modelling



Source: Reproduced from Etienne (2006), Figure 1.

Box 1: Tools and resources for ABM…

Although there are dozens of options for computer software in which ABMs can be developed, three merit special mention because of their widespread use in environment and development contexts.

NetLogo is a high-level, open-source, cross-platform programming language which developed from an educational domain and is now one of the most widely used platforms for ABM research.

Repast (REcursive Porous Agent Simulation Toolkit) was designed with social scientists in mind. It provides a family of open-source platforms allowing different ways of writing models.

CORMAS (COmmon-pool Resources and Multi-Agent Systems) simplifies the task of modelling and simulation within collective learning processes. It focuses on integrated natural resource management issues and is particularly strong on representing spatial aspects.

The scientific community working on these sorts of problems has several organizations and discussion forums. The European Social Simulation Association (ESSA) organizes an annual conference, runs summer schools and provides many Special Interest Groups, as well as the JISC e-mail discussion list on Simulating Societies (SIMSOC). Multi-Agent-Based Simulation (MABS) is an international workshop series which attracts social scientists as well as computer scientists using social analogies to develop software. The OpenABM consortium (www.openabm.org) is a network for researchers, educators and professionals working on modelling. It provides many services, including model archiving.

Some short introductory articles for general interest include a *New Scientist* interview with Joshua Epstein, one of the pioneers of Agent-Based Modelling (bit.ly/1XIGeol) and a paper by the British sociologist Nigel Gilbert (2004), also a pioneer in the use of agent-based models in sociology.

Books on social simulation include Gilbert and Troitzsch (2005), which is still one of the best introductory texts. More recent books include Railsback and Grimm (2011), which is interdisciplinary but includes more examples from ecology, and Wilenski and Rand (2015), which is tied to understanding and using NetLogo. The handbook on social simulation by Edmonds and Meyer (2013) covers about every topic and is a good review of state of the art. Epstein (2007) also covers more advanced material.

…and on complexity

Ramalingam (2013) provides a complexity framing of the development aid system. It is also a good introduction to complexity for general readership. ABM is included among a range of methods (see pages 283-295). Miller and Page's (2009) book on Complex Adaptive Systems is a clear and wide-ranging reference. Norberg and Cumming's (2013) book *Complexity Theory for a Sustainable Future* will also have resonance for readers of this paper. However, this is just a very small sample of the available literature on modelling and on complexity.

Agents are, first, endowed with some initial data and rules, and then simulations are made to investigate the results of their interactions, such as patterns of risky behaviours, or shifts in socio-technical regimes. In other words, ABM is an experimental approach for understanding the consequences of modelled assumptions. This can help to generate new knowledge or novel hypotheses. It can be particularly useful for looking, experimentally, at possible future evolutions of the situation (i.e. for producing a simulation).

Considerable detail can be included in ABM because it models low-level behaviours of actors, their decisions and (inter-)actions. The complexity of the situation can be explored, with different/alternative rule-sets, and with populations of heterogeneous agents. In fact, the early pioneers of ABM found that often just a few rules can generate complexity at the aggregate level. Nowadays users of ABMs argue they can become part of a new generation of models giving a better picture of sustainability problems. Including more detail about human behaviour in this way may allow greater understanding of macro-phenomena than is possible with traditional modelling. Other studies focus on how higher level properties, once they have emerged, enable and constrain what agents are able to do at an individual level – showing micro and macro aspects to be mutually influencing.

There are now a wide range of tools and resources to support an ABM approach (see Box 1). This expertise is growing across multiple disciplines. Here we focus particularly on how social systems can be represented. ABM is a type of social simulation that provides another approach to aid social science research. However, it is also argued that ABM can be used in decision support for responding to emerging (and complex) risks. Nay et al. (2014), for example, discuss decisions related to climate change, where "the ultimate goal is to more effectively determine which (if any) development interventions are most likely to improve communities' welfare in light of the expected climatic change." Some aspects of complexity in particular, such as when there is a large range of uncertainty in potential inputs and when surprising dynamics are at work, are most compatible with the use of ABM.

3. FREQUENTLY ASKED QUESTIONS ABOUT ABM

When researchers are considering whether to use ABM, they often raise basic questions about the need for and utility of the approach. In this section we focus on four frequently asked questions – the answers to which are further illustrated by the examples in Section 4.

3.1 Do I need an ABM?

Probably the most common question asked by those considering the method is whether they actually *need* to use it to tackle a specific question. One school of thought would say that it is best to first consider using a simpler model or other relevant method. The development of ABM is beset by difficulties, practical as well as conceptual, at all stages. Some important ones, drawing from Edmonds et al. (2013) include: the complexity and variability of the social world, which is difficult to render in the abstract; the lack of adequate data (data that we have are vague, uncertain, subjective etc.); inputs to models are usually assumption-based rather than observation-based; simulations are difficult to understand fully*;* and verification (e.g. replication) and validation are difficult. Moreover, it is fair to say that these difficulties are not generally compensated by a high rate of model uptake and practical use (Lucas 2011).

In this light, critical questions should be asked: What do you want to use the model to find out? What could you learn from the process that you could not otherwise find out using another approach? If the focus is on predicting rather than understanding a phenomenon, then it may be better to use different modelling methods. For a discussion of different purposes of modelling, see, e.g., Epstein (2008) and Edmonds et al. (2013). Many people have found ABM useful and informative in exploratory research, for instance, where the question initially is less well-defined. In other situations, the process of creating and using an ABM may shed light on the research question itself, but it may not actually answer it.

ABM is applicable to many sorts of problems and has spread greatly in topical focus from initial areas such as behavioural economics, environmental resource problems and transportation. This is partly due to the flexibility of ABMs and partly due to the relative lack of *a priori* theory. The lack of a strong basis in social theory is sometimes construed as a drawback of the approach.

Moreover, flexibility does not mean ABM is always a good choice. The trade-off in potential benefits against difficulty of ABM is most likely to be worthwhile if there are important interactions that must be included in a disaggregated way. This would typically mean specifying how interactions (e.g. perception or communication) shape the behaviours (and adaptations) of actors in the model's rules.

Therefore, a starting point for ABM is considering who the main actors are – which actors' decisions and behaviours need to be analysed. This can also include the macro-level decisions of policy actors. If a specification of actors and interactions can capture essential aspects – and details – of the situation, then it may be useful to use ABM. Another indicator is if small changes in these details are thought to produce a much larger effect, for instance, non-linearity.

A strength of ABM is the consideration of dynamics among agents and model variables. Dynamic processes specified at the micro-level can be investigated to discover how other dynamics are produced at more aggregate scales or over longer time frames. ABM is not the only simulation method useful for understanding dynamics. System dynamic models (SDMs) capture some of the feedback cycles between the key factors, doing so in a more aggregate way – using fewer units. SDM has been applied to similar areas of economics and natural resource management, since the iconic 1970s *Limits to Growth* model (Meadows et al. 1972). The SDM "stocks and flows" concept has been successfully applied in diverse research areas, including water management planning, as the basis for SEI's WEAP (Water Evaluation and Planning) system.[1]

Problems involving dense, decentralized interactions, feedbacks, and uncertain and surprising phenomena, on which no other method is likely to provide satisfactory insights, are the ones for which ABM is most useful. Still, from a practical point of view, it can easily take a year or longer to design, implement, and finally – and most laboriously – analyse the model. An important factor is that resource demands are quite intensive for ABM development and use. Thus, if you have the time and available resources, using ABM as part of your "toolbox" will help you paint a richer picture of the subject of your research and aid understanding.

3.2 Are there good examples of ABM applications to learn from?

Over the last two decades or so, many thousands of ABMs have been made. Perhaps only a few dozen, however, have been maintained, reused and empirically updated over a longer term. Generally it is quite hard to find totally relevant examples. Literature on ABM is quite fragmented, and a search of bibliographic databases may not yield results; however, helpful responses may be collected through professional channels such as the JISC e-mail discussion list on Simulating Societies (see Box 1). Many areas of environment and development have not been studied at all with ABM. In other cases, examples can be found which capture part of the problem or focus on different but related phenomena. Users have to judge whether these are sufficiently relevant to the particular issue they wish to investigate.

On the other hand, there are some very successful examples and established application areas for ABM. Examples include Lansing and Kremer's (1993) Balinese rice irrigation model, ecosystem management applications (Bousquet and Le Page 2004), or a growing body of work on climate change adaptation. Where research converges on similar questions, much can be learned through review and comparison of models.

Learning from existing models is complicated by the fact that most are bespoke and are not reported, archived, certified and made available in a systematic way.

[1] See http://www.weap21.org.

However, code is increasingly being made available for many models (see, e.g., http://www.openabm.org). Where existing models are available, the “TAPAS” (take a previous model and add something) approach is highly relevant. Its incremental approach to generating new knowledge can be very useful, but the conditions of applicability for an adapted model must be assessed to understand whether the “something” added has not invalidated the original model. This points to the fact that all models (especially empirically informed ones) have limited transferability. To what extent can we and should we generalize with models? Here it is worth pointing out the danger of assuming that a model designed for a particular context will be applicable in other situations.

While the trend in ABM work has not been towards generalization (with all its concomitant difficulties), it has been moving towards more empirical detail that can, in particular contexts, deliver useful new knowledge.

Linked to this is a question about examples of ABMs that have actually been used to support policy decision-making or for other purposes "in the real world”. As mentioned above, there is not a high rate of model uptake and practical use. Partly this is because ABMs do not supply predictions and simple recommendations, but from a decision-making perspective they supply uncertainty and therefore are not perceived as reliable. Another part of the explanation may have to do with how decision-makers and eventual users of the model are brought into the research process. Whether they are developing a new model or adapting an existing one, stakeholders are an important source of knowledge and ideas. The use of participatory methods can have many benefits, as explored below. Chief among these is that they can help develop the utility of those models.

3.3 Is ABM a stakeholder engagement method?

A question that interests many applied researchers is whether or not ABM is a suitable method for including stakeholders in research and in actually co-producing relevant knowledge with participants. Stakeholder engagement takes many forms and is important not just for eliciting data. Co-creation affects outputs in multiple ways: for legitimizing, providing transparency, and making research relevant to end-users. ABM can claim – and this is in line with our experience at SEI – to have an intuitive mapping to real social actors and to be easier for people without any background or training in modelling to understand how a model works. That is to say, it is much easier to understand model assumptions in an ABM in comparison with other models which are dominated by mathematical expressions. A pedagogic example would be the Lotka-Volterra equations used in predator-prey models which can equally be modelled in an ABM. Moreover, fieldwork suggests that among less formally educated and literate groups, there is a high level of understanding and interest in contributing to discussions about the models. So the answer is an emphatic yes: participatory modelling can be used as a stakeholder engagement methodology.

Still, some stakeholders may be better positioned than others to participate fully in ABM development. First, although general domain knowledge is important, specific knowledge of micro-rules and decision factors allow them to uniquely give inputs to and influence the research. Second, it is helpful to have an appreciation of complexity thinking and terminology to describe what is observed (trends and thresholds) and to discuss the challenges (trade-offs and feedbacks). This is not as unlikely as it may sound – most stakeholders have a high degree of knowledge of the complexities of their own domain and are good at modelling it mentally. Third, familiarity with statistical methods and skill at detecting patterns can also be important in understanding a model and its quantitative outputs more comprehensively. Finally, communication skills are important. Models are often used to communicate an idea;

concept diagrams, images and a strong narrative can help better illustrate the idea and – in conjunction with a computer model – make it a more interesting and powerful experience.

Stakeholder feedback meetings benefit from giving a demonstration of the model or showing a video of the model running. Participants are good at spotting visual patterns and inconsistencies (what is good, or wrong, about a model); a useful approach is asking directly for such feedback. There are many ways of visualizing ABM results – these should adhere to design principles that make them more understandable (Kornhauser et al. 2009). Interactivity, such as game-like elements, can also help to engage an audience.

A potentially useful approach, relevant here, is using different types of modelling with different stakeholders: combining bottom-up and top-down approaches (Forrester et al. 2014). Indeed, there are several other modelling approaches – Bayesian belief networks, fuzzy cognitive mapping – to which similar arguments are relevant.[2] These methods are also potentially very useful stakeholder engagement tools, but beyond the scope of this paper. With all types of models, care has to be taken with model interpretation: for example, ensuring that stakeholders do not over-interpret model outputs or put too much store in their reliability. Other aspects of modelling can be easily overlooked such as how uncertainty and risks are presented in modelling.

Pioneering participatory ABM, the "Companion Modelling" group (http://www.commod.org) addresses the exchange between co-production of knowledge and support of collective decision-making processes. For them, the inclusion of stakeholders is meaningful because participatory modelling is about the "co-construction of conceptual models that represent visually multiple viewpoints and can be employed as mediating, discursive objects that promote collective learning processes". Benefits of participatory ABM are recognized: Barreteau et al. (2013) discuss three types: (1) the quality of the simulation model itself; (2) suitability of the simulation model for a given use; and (3) participation support – i.e. raising awareness and/or social learning about a situation.

Point (3) about participation support emphasizes a view that attaches an equal importance to the process as to the outcome of the engagement. The "ownership" of the process by stakeholders can, as with other participatory methods, be crucial for them moving from a more passive role as advising (providing knowledge, values and ideas that are relevant to decision-making) towards an organizing role, reflecting on the information generated and identifying realistic and relevant solutions (Lonsdale 2011). This includes the opportunity to represent their views and ideas to others – for example, bridging different levels of decision-making and governance.

3.4 Can ABM be used in conjunction with other methods?

Some researchers may wish to use ABM as part of a larger project that also applies other methods. Is this feasible, and what sorts of data requirements arise when ABM is added to a project? These questions should rightly come at a more advanced stage of consideration, but they are still important for getting modelling research off the ground. Since modelling only captures partial features of a research issue (describing a specific part of the system or looking at it from a particular standpoint; see Zeitlyn 2009), it is also necessary to include other methods to understand the full context of the situation.

[2] For brief overviews, see https://www.weadapt.org/knowledge-base/adaptation-decision-making/bayesian-network and https://www.weadapt.org/knowledge-base/adaptation-decision-making/fuzzy-cognitive-mapping.

Qualitative methods highlight the local realities and show what is important to communities and other decision-makers, revealing cultural factors, institutional factors, etc. Scoping studies and initial assessments can better indicate what is important to include in modelling activities and what can be left out – or can be delegated to background assumptions. These can include primary data collection methods. Narrative data provide very rich information and can be a good source of ideas for modelling, but it is generally difficult to transform this into a suitable format to include in a model. There are no standard techniques for qualitative data integration, although it is a recognized methodological issue (see JASSS Special Issue introduced in Edmonds 2015).

Quantitative methods, on the other hand, can normally be used more directly in modelling. According to Poteete et al. (2010, p.196), empirical inputs can be obtained from (1) stylized facts, (2) laboratory or field behavioural experiments, (3) role games or (4) case studies. These activities are most often designed to produce quantitative data that inform models through, for example, parameter estimation or initialization of agents' state variables.

Relational data are often very important inputs to modelling. Methods that deal specifically with spatial relations, such as geographical information systems (GIS), and social relations, such as social network analysis (SNA), can be usefully integrated with ABM. This has been simplified with development of software libraries/packages for importing and editing such data within ABMs. Note that all three types of data mentioned – qualitative, quantitative and relational – are also often used in model validation, an important step in establishing that a model is credible in explaining some aspects of the world around us. It is worth looking in more detail at how some of these methods relate with ABM.

A key similarity between SNA and ABM is the focus on individual actors and their interactions, which are modelled directly at the micro-level. SNA practitioners may ask, "Are the characteristics of an actor correlated with its position in the network?" Those using ABM, in turn, may ask: "What are the wider consequences of their interactions?" (e.g. patterns or trends of risky behaviours, resource depletion etc.). A key difference is that SNA provides more of a snapshot study of actors and relations (at given place and time), whereas ABM is useful to generate and interrogate dynamic scenarios for a situation. ABM scenarios, based on different model assumptions and parameters, are simulated to investigate temporal patterns and compare outcomes (including changes in networks). There are qualitative, as well as quantitative, methods for the study of social networks that have been successfully used. A participatory version of SNA, Net-Map (netmap.wordpress.com) is used quite widely, and similar techniques have been integrated into ABM processes. The utility of qualitative social network mapping is further discussed in the context of natural hazard-related disasters in Taylor et al. (2014).

Similarly, the ARDI process (Etienne et al. 2011) generates qualitative and quantitative information following a set of steps conducted in a facilitated workshop/focus group setting. This allows the production of information directly useful in model development, where targeted questions can be asked about relevant interactions, trends and dynamics related to resource management problems. Further, knowledge elicitation tools, or KnETs (see ABM Case study 2 on Cameroon) is a complementary method to understand actors' decision making in the context of the interaction of a range of salient drivers.

Participatory GIS, SNM and KnETs could also be described as mixed methods. They are used for constructing empirical evidence: that is, knowledge generated from observation and/or interviews with decision-makers. Mixed methods approaches combine data and methods which may originate from different disciplines and world views, and they must tackle the further complication this implies, such as the questioning of underlying assumptions. Mixed methods also address the trade-off between the desirable formal characteristics of qualitative data that are useful in modelling, and the diversity of responses and considerable detail elicited using qualitative methods. By structuring information collected on the ground, they can contextualize an ABM and substantiate certain model assumptions and parameters. The continued development of such methods will be very important for ABM to become a reliable, trusted tool for informing sustainable development decisions.

4. CASE STUDIES OF ABM APPLICATIONS

In this section we present four examples of applications of ABM as part of recent SEI projects. We explain how the models were used and briefly discuss the extent to which issues covered in Section 3 arose in these projects.

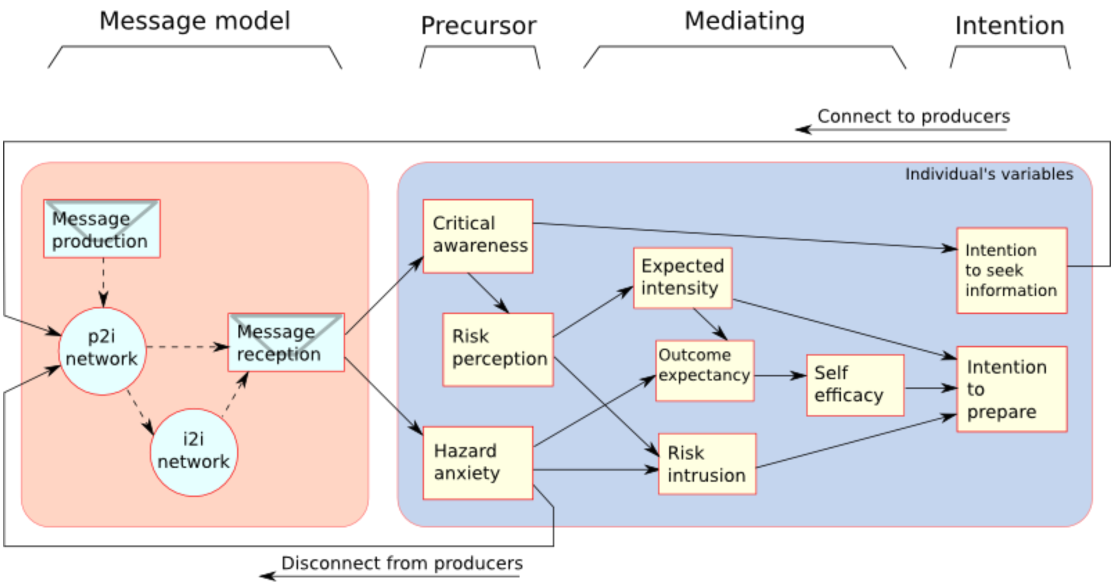
4.1 Earthquakes in Turkey: Disaster preparation and community resilience

Disaster management situations are often described as complex, given their unpredictability and sensitivity to particular circumstances, as well as the interconnectedness of different disaster actors and resources. A literature review showed that some work has used ABM to understand emergency response in disaster situations, particularly evacuation, or to model the preparedness of authorities (emergency services, civil protection, etc.). However, a novel application area addresses community responses to disaster risks – the behaviour of civilian individuals and households, for example. The emBRACE project (http://www.embrace-eu.org) provided an opportunity for development and improvement of methods for modelling disaster resilience (at the municipality, organization or city level), tested through application within case studies.

Our modelling used a TAPAS approach. An ABM was based on Paton's (2003) conceptual model of socio-cognitive factors affecting disaster preparedness. The model posits how motivation factors affect formation of behavioural intentions – "intention to prepare", and "intention to seek information" – and how intentions interact with other personal-level variables and social factors, mediating the decision to adopt preparedness behaviours. Hazard anxiety, one of the model variables, has been empirically found to influence this process in contradictory ways. Some level of anxiety seems necessary to promote intentions to prepare; on the other hand, high anxiety can be overwhelming and may trigger hazard denial as a coping mechanism.

Dynamics and feedbacks are not explicitly considered in Paton's model. An ABM can extend this by adding new assumptions about the dynamic interplay among variables in this system, and among the actors. This involved specifying how change in one variable triggers change in another. The results showed that different categories of behavioural response were generated, which, it was argued, could be an important distinction to consider when considering timeframes of real interventions. Then, based on a case study of earthquake-related disasters in Turkey, we carried out simulation experiments using scenarios related to national insurance planning. The analysis suggests that insurance interventions could have a positive influence on pro-preparedness intentions if they limit the hazard denial phenomenon. Thus, in this example we faced issues surrounding searching and using other models as well as appraising the added value provided by the use of ABM.

Figure 2: Disaster preparedness model conceptual diagram, showing key model variables and relationships



4.2 Adaptation and mitigation for agroforestry livelihoods in Cameroon

A model was developed to simulate farmer decision-making in response to multiple drivers in forest areas in southeast Cameroon. Livelihoods in this region depend upon a mix of cash crop and subsistence farming, together with complementary forest activities (Devisscher et al. 2013). Declining soil fertility and quality, changing climate and an increasing human population, have often led to agricultural expansion for cash crop cultivation. The sustainable development challenge is to look for solutions that resolve the conflict between livelihood needs and policy needs, including national climate change mitigation efforts.

Cocoa production is a main income-generating activity for most households, and performs well compared to other cash crops in a less favourable climate. Grown within a partial shade system, this agroforestry system can also support carbon capture and is potentially eligible for REDD+ financing.[3] This is an example of co-benefits: shaded cocoa systems, together with improved agro-forestry, and soil and water conservation techniques, could provide benefits for both climate mitigation and adaptation. However, if all farmers continued expanding cocoa plantations at the expense of forest, that would be a form of maladaptation, with costs that would outweigh the mitigation and livelihood benefits.

In the context of this complex situation, the objective of the ABM is to better understand conditions that could lead to successful adaptation or, conversely, maladaptation. Knowledge elicitation tools (Bharwani 2006) were used to develop decision rules based on a statistical (machine learning) technique which is applied to qualitative data collected through KnETs "game interviews". This provided rules characterizing choices for poorer and for better-off farmers, some of which were included in the ABM (Bharwani et al. 2015; see also Figure 4). During interviews, participants can explain and clarify their choices, allowing information to emerge – often tacit information – which is additional to the game.

[3] Reducing Emissions from Deforestation and forest Degradation (REDD) is a mechanism that aims to mitigate climate change through enhanced forest management in developing countries.

Data from KnETs were complemented with other qualitative and quantitative local information together with scientific data incorporated using GIS and forest cover data (shown in Figure 3) to a resolution of 30x30 metre grid cells. This allows the representation of micro-decisions of farmer agents, such as their crop choices or decisions to expand cocoa farms or to implement improved agroforestry practices. Indicators of the performance of the livelihood strategies are computed on the household level to inform agents' choices in the model. At the aggregate level, various statistics are used to show model outcomes such as overall forest cover, soil fertility or food security. Thus, this example illustrates the use of other empirical data and methods as well as participatory stakeholder research.

Figure 3: Bird's-eye view of model showing GIS lines, forest cover data

Light greens represent high-cover areas, dark greens represent low-cover areas, and circles represent forest farming.

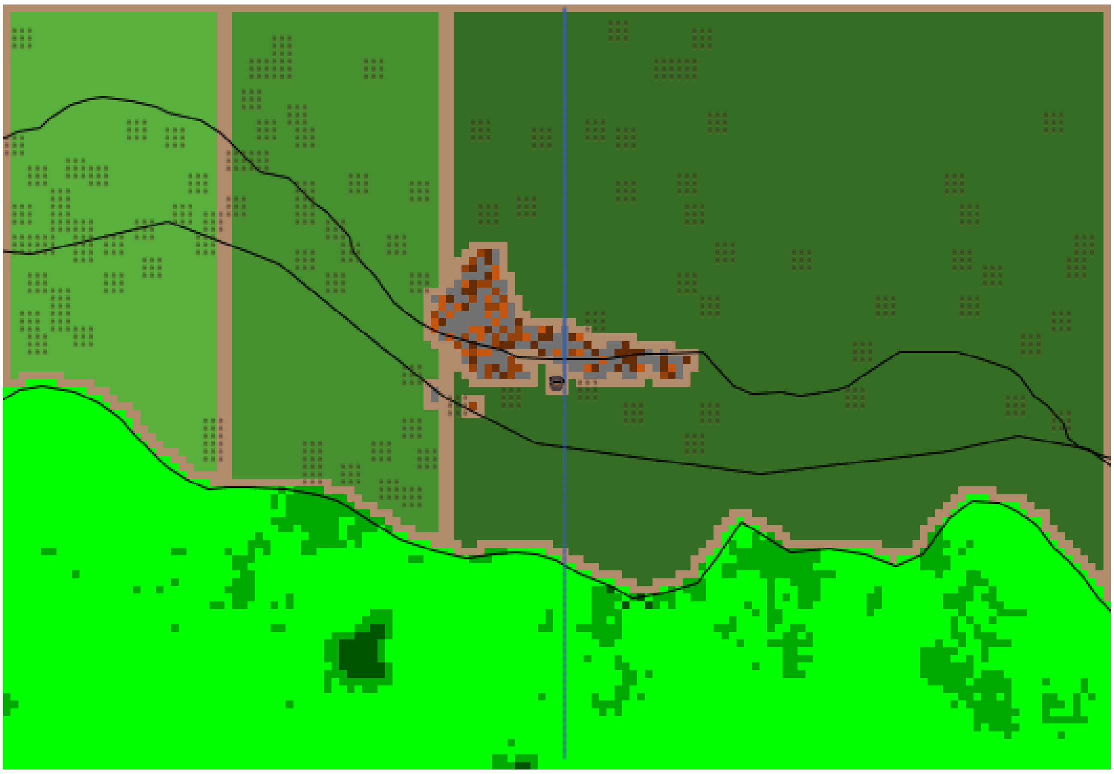
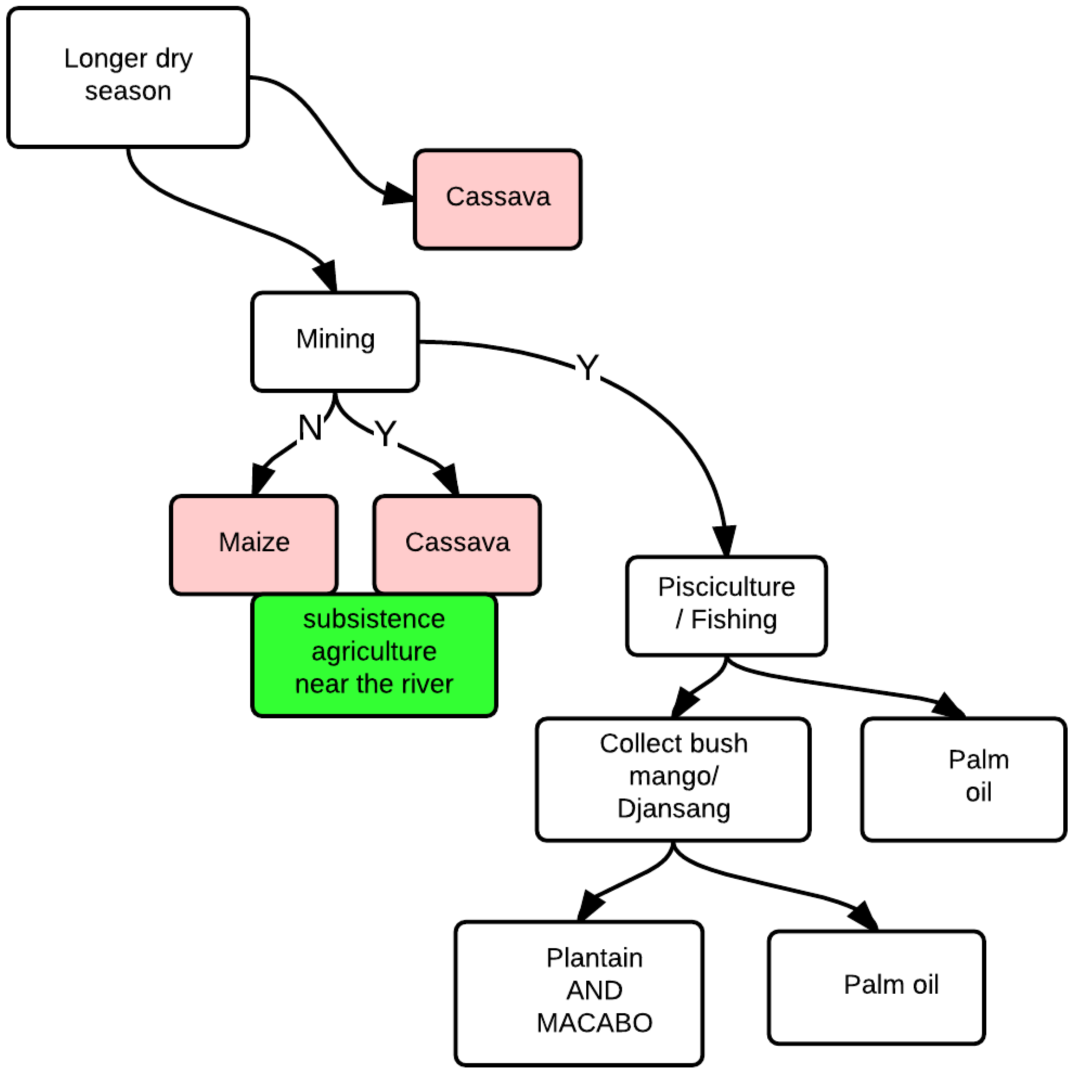


Figure 4: Example decision tree, produced with KnETs, showing heuristics in better-off households.

Tracing through the tree shows which drivers are required for each of the possible outcomes. In this case, "if there is a long dry season" THEN "I would do artisanal mining" AND "pisciculture" AND "I would grow palm oil".



4.3 Transitions to biodiesel in Malaysia

Social simulation models have been used to look at innovation policies for and transitions to sustainability across and among different sectors (such as water, energy and agriculture). Questions are addressed using different economic modelling methods, including both micro and macro approaches and multiple stakeholder perspectives (see http://transrisk-project.eu/). System dynamics models can help with understanding transition processes and pathways. The example for Malaysia (shown in Figure 5 below) explores challenges in the sustainable development of a national biodiesel industry.

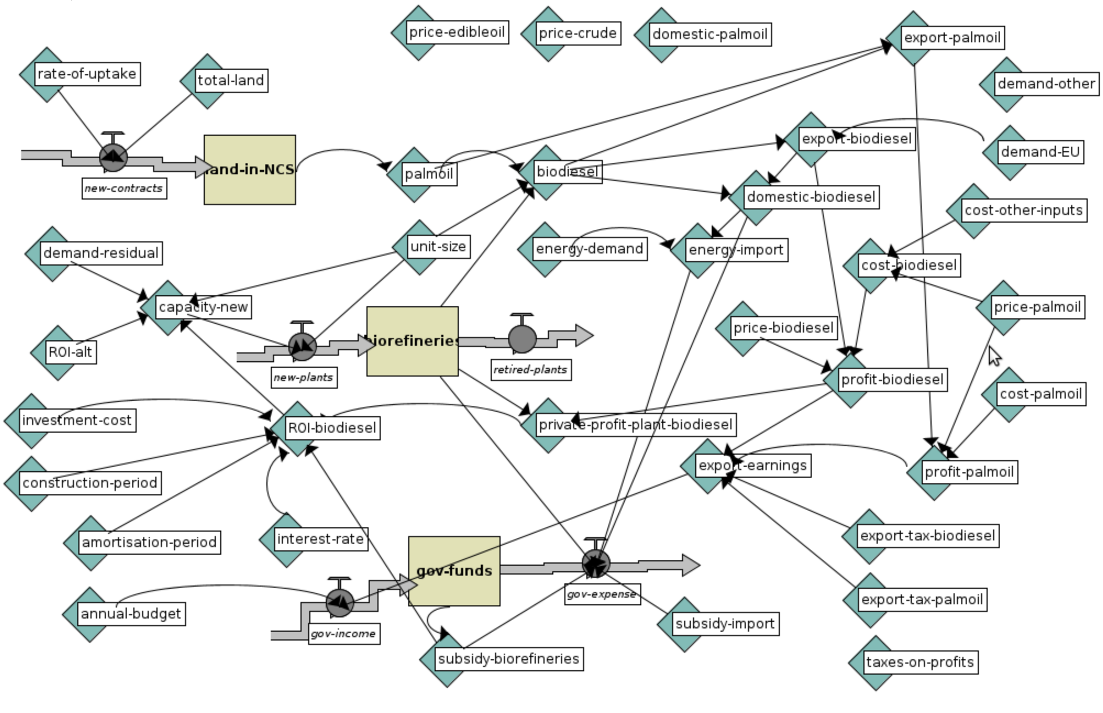
Malaysia is the world's second-largest palm oil producing country, after Indonesia. The palm oil industry is a key potential export earner and is important for meeting growing domestic energy needs (by replacing imported petroleum products with biofuels). However, low prices for crude oil and for palm oil in the past five years have slowed the development potential for biodiesel. Exogenous trends, together with weak environmental regulation, has manifested in risks to the sustainability of local livelihoods and environment. Thus, policy-makers are faced with a trade-off between incentivizing actors (firms, community groups, etc.) to generate long-term benefits, and the risks associated with potential external shocks or trends. Government intervention includes a policy mix of subsidization, bioenergy mandates and international agreements, such as the recently announced Indonesia-Malaysia Council of Palm Oil Producer Countries.[4]

The model shown here can be used to compare different strategies and to explore/compare different scenarios for crude oil price, palm oil price, and biofuel price (all of which are externally determined). The model shows interaction of three key stocks: the land under palm plantations, biodiesel production facilities (plants), and the national energy fund. The model operates on an annual time-step for decision-making, in which the government is able to set the tax rate and set the subsidy, in order to balance expenditure and, over the longer term, grow the (infant) national biodiesel industry.

System dynamics model design is based on a study in Malaysian Borneo (Devisscher 2009). This initial work with SDM allows model simplification – for instance, the formulation of investment decisions as a single equation. It illustrates using social simulation to relax the (neoclassical) economic assumptions typically used in macro modelling approaches and the potential to show transition dynamics with SDM or with ABM. Thus, this example relates to the selection of appropriate modelling techniques; social simulation is becoming established in societal transitions research.

Figure 5a: Visualization of model structure

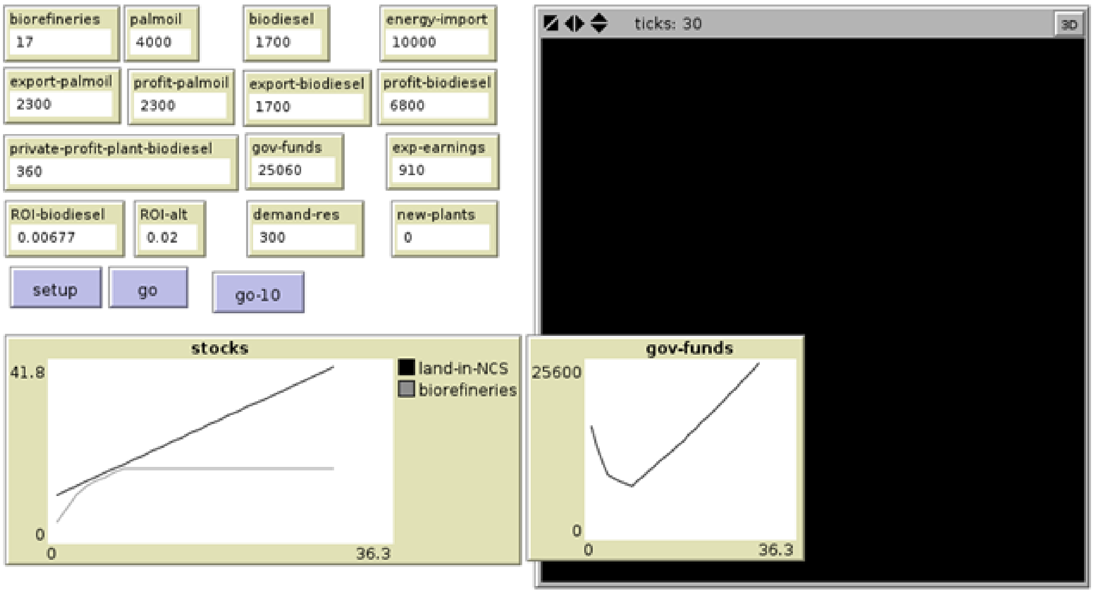
The figure shows stocks (boxes), flows (thick arrows), variables (diamonds) and their links (thin arrows).



[4] See http://www.indonesia-investments.com/news/todays-headlines/indonesia-malaysia-set-criteria-for-the-council-of-palm-oil-producer-countries/item6697.

Figure 5b: Output of a simulation experiment where subsidy to bio-refinery construction is high

A high return on investment attracts initial take-up in the industry. However, the government goes into debt for one time-step and withdraws the policy, with funds taking longer to recover.



4.4 Piloting local fishery models on the Kenya's southern coast

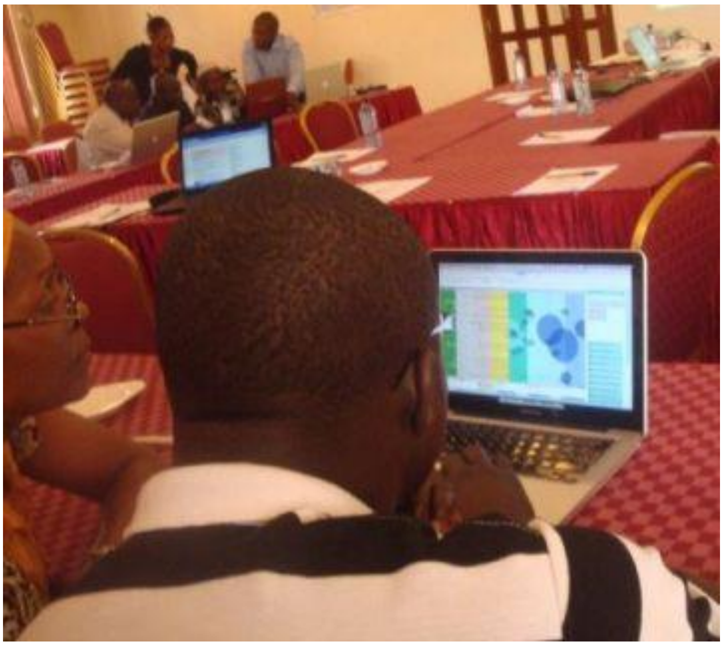
As part of a project about decision-making in coastal ecosystems, we modelled artisanal fisheries on the southern coast of Kenya. The governance context for fisheries in Kenya has changed recently. Starting around 2007, responsibility was handed over to a new type of village-level organization called the beach management unit (BMU), with the aim of improving management of productive fisheries around the reef ecosystem. Another change is the devolution of responsibility for policing the use of different fishing gears where the legality is contested.

The methodology borrowed from participatory modelling approaches and, through a process of including different coastal stakeholders, several pilot model iterations were made. Models included local information about the role of BMUs, information about fishing grounds and landing site, and about use of fishing gears and vessel types. We tested the models in different facilitated workshops and meetings where we received a great deal of feedback. Stakeholders included the local- and district-level users and managers. At the end of the project, stakeholders were interacting with the models themselves, configuring options which allowed them to construct game scenarios. Partly, the research allowed local issues and perceptions to be highlighted and raised at the district level. It also allowed local groups themselves to raise awareness among their own community (Forrester et al. 2014).

The project drew some observations on what factors helped or hindered the project. Most of the lessons relate to what was seen as a good/obstructive process and facilitation, rather than to the merits/limitations of the ABMs itself. For example, we found it was important to work closely with opinion leaders, such as BMU leaders and their representatives, as well as with expert researchers in the Ministry of Agriculture, Livestock and Fisheries. Similarly, inviting people with different occupational backgrounds and roles, including women's groups and environmental stakeholders, helped to get a wide range of perspectives. It was found that models could facilitate knowledge transfer through discussing and feeding back these viewpoints at different decision-making levels and between modellers, local researchers and students.

In conclusion, while they can initially be difficult to understand, ABMs can also be very appealing to those who are engaged with resource management and with resource users themselves, particularly if the models are seen to have local relevance. Pilot models, built for thinking about the issues, rather than more fully developed and analysed models, can be good enough to promote discussion, knowledge exchange and learning, if they are also backed by good facilitation processes. This example heavily involved stakeholder feedback, and it also draws lessons about comparing ABM with other modelling approaches used in parallel.

Figure 6: Participants testing the fishing scenarios during a workshop



5. CONCLUDING COMMENTS

Policy-makers want timely solutions that can work within existing policy contexts. They also want tools that can be generalized to different situations. ABMs, however, often need to be built – and understood – from scratch. They produce findings that are not easily transferable, and outputs that can appear to be quite difficult to understand. Policy-makers value conciseness and may prefer simple indicators, not complex, multidimensional, and disaggregated information produced by ABMs (as well as information about uncertainty).

However, modern policy-making is also much more complex than it appears. Scientific assessments may be able to greatly benefit from using ABM. Solutions tested in an ABM can be quite complex: adaptive actions such as policy withdrawal or policy-corrective strategies for “wicked policy problems” (Forrester et al. 2016) can be simulated. A key strength of ABM is that it can include more detail and context than other modelling approaches. Models can be used to explore different trade-offs and interdependencies among policies, and different scales of decision-making, also including important micro-level priorities.

Moreover, in ABM, the time dimension is explicitly acknowledged, which is crucial when assessing sustainability. ABMs can allow us to conduct a deeper investigation of different scenarios for sustainability, by simulating the consequences of actions or measures taken and analysing conditions under which they may do well. They allow us to better understand how people may adapt differently to different types of interventions, in the long and the short run, and how their vulnerability and resilience may change. Such scenarios can be derived directly from case studies, field work investigations and stakeholder priorities.

Examples of ABMs that have actually been used to support policy decision-making or for other purposes "in the real world" are increasing, though it is still not a mainstream method in university science departments, not to mention in the offices of policy advisors and think tanks. On the other hand, it is fair to say that ABM is now quite well regarded as a relevant and valid scientific method, although still lacking rigour in how models are tested and results communicated. The extent to which ABM will be adopted outside of academia also depends on whether it will be viewed as a trusted, legitimate and practical method by those applying it. In an environment and development context there are often very significant knowledge gaps and complexities to come to terms with. We have found that ABM is a powerful tool to address complexity when it is used along with other methods.

In conclusion, we have been arguing that one cannot address complex problems with simple solutions. Complexity tools explain complexity. The aim of this paper is to illustrate that methods and tools are available that help to get this message across. At the end of the day, ABM should be evaluated in comparison to other modelling approaches. ABM provides results and dynamics that are not possible to produce with standard modelling approaches. In particular, ABMs may be preferred to more mathematical, aggregate models for they bring greater opportunities for interaction and co-creation. Such modelling helps to structure people's understanding of the situation. Both the modelling process and model outputs can help to clarify and to communicate that understanding.

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